RESTORATION OF TEXTURAL PROPERTIES IN SAR IMAGES USING SECOND ORDER STATISTICS

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Abstract

Local second order properties, which describe spatial relations between pixels are introduced into single-point speckle filtering processes, in order to account for the effects of speckle correlation and to enhance scene textural properties in the restored image. To this end, texture measures originating, first from local grey level co-occurrence matrices (GLCM), then from the local autocorrelation functions (ACF) are used. Results obtained on L=3-looks ERS-1 images illustrate the performances allowed by the introduction of these texture measures into structures retaining speckle filters.

1. Introduction

Texture, which is concerned with the spatial distribution of grey levels, is known to be important in analysis of SAR images for a wide range of applications. In most of these applications, radiometric and textural information is retrieved after SAR image adaptive speckle filtering.

Nevertheless, in the most usual current adaptive speckle filters [1-4], the filtering process is controlled by the local coefficient of variation C_R of the scene R, through the local coefficient of variation C_I of the image I and a multiplicative uncorrelated speckle model using only first order statistics [5].

The coefficients of variation are statistically [1] sensitive to texture and speckle noise strength [6], but provide no information on texture directionality, and limited information on speckle correlation. Therefore, second order statistical properties must be also considered for a complete restoration of the radar reflectivity, including both scene texture and resolution/sampling related phenomena. These statistics are used explicitly in the multiple-point linear minimum mean square error (MMSE) filter developed by Kuan *et al.* [3], and could be introduced in the Wiener filter developed by Frost *et al.* [4], following the scheme proposed in [7], and implemented later by Quelle & Boucher [8].

Usual single-point filters, do no explicitly use second order statistical properties, and texture is preserved only due to the spatial variation of the local first order statistics, using a non-stationary mean non-stationary variance (NMNV) formal model [3] based on the observation that tone and texture depend on each other.

In this paper, local second order statistical properties are explicitly introduced into (or after) the speckle filtering and radar reflectivity restoration process, using either Haralick features [9] of the local GLCM, or for more completeness the local ACF. The desired effect is to account for correlated speckle and to enhance the restoration of textural properties in the filtered image.

2. Single-point speckle filtering using second order statistics

Second order statistics have explicitly been used by Quelle & Boucher [8] in a single-point filter. Estimation of the frequencial characteristics was done in the speckled image at lags of one pixel only in range and azimuth, thus mainly limiting the description of correlation properties to those of the speckle.

In all other cases [1,3], the development of a filtering method using second order statistics, i.e. an estimation of the complete ACF of the scene through the speckled image ACF, results in a vectorial equation giving rise to a multiple-points filter.
To avoid this complication it is highly desirable to introduce an adequate description of speckle correlation properties and spatial relations between resolution cells into single-point speckle filters.
This can be done if we consider the NMNV model, by introducing local second order statistics to refine the computation of the local NMNV first order statistics. This way, speckle correlation properties could be taken into account for filtering purpose. On a given textured class of the scene, when scene correlation length is smaller than the processing window size, the mean radar reflectivity $<R>$ will then be modulated by the scene ACF, i.e. the correlation length in all the possible directions. When scene correlation length is longer than the processing window size, the longer the correlation length, the closer to the classical ML estimate $<R>\approx I$ the estimate for the non-stationary mean radar reflectivity.

3. Using local grey levels co-occurrence matrix (GLCM)

An important aspect of texture is concerned with the local spatial dependence among the grey tones. The texture of an image R(a,r) can be analysed by the GLCM which is the joint pdf of the pairs of grey levels that occur at separation $S=(\Delta a$ in azimuth, Δr in range). This joint pdf takes the form of an $n \times n$ array P_S, where $P_S(i,j)$ is the probability of the pairs of grey levels (i,j) occurring at separation S. The GLCM has the particular property that texture directionality can be assessed by comparing measures of spread of the values of the GLCM around its main diagonal for given directions S.
Haralick has proposed a variety of features that can be used to extract useful textural information from local GLCM's [9]. A number of these Haralick features have been proved quite efficient for textural characterization of terrain classes in optical [10] and SAR [11] scenes.
The concept of textural filtering, introduced by Wang *et al.* [12] to enhance the performances of texture measures, can be applied in a simplified way to the estimation of a very local (non-stationary) mean radar reflectivity M dependent on local texture.
In order to consider scene texture only, the textural filter is applied on a radar reflectivity image, after speckle reduction by means of an adaptive speckle filter. Of course, the speckle filter must be able to retain some local fluctuations of the radar reflectivity, which justifies that only adaptive speckle filters, preferably associated with structure retaining processes [1,2], are suitable for this operation.
For our purpose, M is computed using the "mean" texture feature, describing the nature of grey levels transitions when the processing window moves in the image. The Haralick GLCM "mean" texture feature is defined as follows :

$$M = 1/N \cdot \sum_{i=1}^{n} \sum_{j=1}^{n} \hat{R}(i) \cdot P_S(i,j) \qquad (1)$$

where the choice for $S=(\Delta a,\Delta r)$ depends on the spatial SAR resolutions (i.e. the size of the resolution cell) and on the spatial

sampling rates (i.e. pixel dimensions) in range and azimuth directions, using a processing window size of N=5x5 pixels.
The main drawbacks of this approach are : i) that speckle correlation due to the relationship between system resolution and spatial sampling is ignored during the speckle (MAP or MMSE) filtering process; ii) that texture analysis and speckle filtering (both associated with structures detection processes) steps should theoretically be done in the reverse order for better performances, in order to avoid some blurring of scene structural elements; iii) the precision achieved for $P_S(i,j)$ matrix elements using 5x5 pixels samples is questionable.
Nevertheless, the textural filter performs a spatial redistribution of the backscattered energy (i.e. the radar reflectivity of the scene). Test (cf. §6) will show that it enhances medium scale texture preserved by adaptive speckle filtering.

4. Using local autocorrelation functions (ACF)

Spatial relations between pixels are better described by the ACF, described in a discrete way by a set of correlation coefficients $\rho(\Delta z)$, where $\Delta z=(\Delta a,\Delta r)$. The ACF of an intensity SAR image $\{\rho_I(\Delta z)\}$ is a composition of the underlying scene ACF $\{\rho_R(\Delta z)\}$ convoluted with an overlap function which depends on the point spread function (PSF). Since we adopt a stochastic view that the ACF of the image characterizes the properties of the underlying scene ACF [13], the two assumptions of spatial stationarity and ergodicity are required. To fulfil these conditions, local ACF's must be estimated provided that edges and structures of the scene have been locally detected, when selecting the spatial domain of interest D around the pixel under treatment.
The local estimates for the correlation coefficients $\rho_I(\Delta z)$ are first computed on the domain of interest D. The contribution of the underlying scene texture must be separated from that of the texture due to speckle for all displacements Δz. The underlying scene ACF is deduced from the image ACF, using the following transformation [5] :

$$\hat{\rho}_R(\Delta z) = [1 + \hat{\rho}_I(\Delta z) \,.\, C_I^2] \;/\; [1 + |G_c(\Delta z)|^2 / L] \qquad (2)$$

The normalized ACF of the individual 1-look complex amplitudes $G_c(\Delta z)$ depends only on the SAR complex PSF. It is realistic to adopt an exponential form for the ACF of the speckle for the separated looks detected in intensity :

$$|G_c(\Delta z)| = \exp\,[\,-\,(\Delta a.dx/rx + \Delta r.dy/ry)\,] \qquad (3)$$

where *dx*, *dy* are the pixel dimensions, and *rx*, *ry* are the spatial resolutions in azimuth and range directions.
The computation of a local non-stationary estimate of $\langle R\rangle$ is performed by a simple convolution of the domain of interest around the pixel under consideration by the normalized ACF of the textured scene $\{\rho_R(\Delta z)\}$.A local energy scaling factor ensures the preservation of the absolute level of the radar reflectivity.
This method is closely related to the notion of "texture fields" introduced by Faugeras & Pratt [14]. Considerations on the accuracy of correlation coefficients estimates can be found in [15].

Injecting the estimate M for non-stationary <R> and C_R into the scalar equation of the single-point adaptive speckle filter allows better restoration of natural R fluctuations. The method is complete since speckle correlation is also accounted for.

5. A simple upgrade for existing speckle filters

According to the experience acquired from §3 and §4, it is possible, for oversampled SAR images, to design very simplified heuristic filters derived from §4 for visual enhancement of filtered SAR images, using spatial relations between adjacent filtered pixels.
We can choose to stress one of the following aspects :
1) global effects of spatial sampling/resolution;
2) local correlation between resolution cells.
If R is considered an autoregressive process, its ACF decreases exponentially with distance. This is a plausible and also simple model which, in practice, has been found particularly convenient in the case of SAR scenes [4,16].

1st case : A first order exponential filter, can be applied on a 3x3 pixels neighborhood.:

$$M = K \sum_{\Delta a=-1}^{1} \sum_{\Delta r=-1}^{1} m(\Delta a,\Delta r).R(\Delta a,\Delta r) \qquad (4)$$

Its constant impulse response $m(\Delta a,\Delta r)$ is designed as to verify :

$$m(\Delta a,\Delta r) = \exp(- \alpha.|\Delta a| - \beta.|\Delta r|) \quad \text{with} \quad m(0,0)=1 \qquad (5)$$

where α and β are the autocorrelation parameters. K is a normalizing constant that preserves the mean radar reflectivity. The autocorrelation parameters α and β shall verify :

$$m(rx, 0) = m(0, ry) = 1/e \qquad (6)$$

This filter allows to smooth the "crumbled paper" effect introduced by the structure detection process in presence of correlated speckle, thus enhancing the visual aspect of filtered SAR images. Very limited blurring effect was observed on real structures and textural features.

2nd case : Since different types of terrain are characterized by different values of the parameters R and C_R^2, one can design a first order exponential filter whose impulse response function is (cf. modified Frost filter in [6]) locally adaptive :

$$m(\Delta a,\Delta r) = K_1 \exp[-K.C_R/(C_{Rsup}-C_R). \sqrt{\Delta a^2+\Delta r^2}] \qquad (7)$$

The K parameter governs the width the impulse response, and can be fixed considering the sampling rate. C_{Rsup} is a threshold allowing to preserve strong scatterers responses [6]. K_1 is a normalizing constant that preserves the mean radar reflectivity.
Smoothing of undesirable effects and visual aspect enhancement is performed without apparent texture and structures degradation.

6. Application to ERS-1 SAR images

Fig. 1 shows the 3-looks FDC ERS-1 image of the area of Seville (Spain), on which filter's modifications are tested. This image has a resolution of about rx=30m, ry=30m, whereas the pixel size is dx=16m, dy=20m. Speckle correlation due to excessive oversampling of the radar signal, (even more pronounced in PRI images) affects the performances of adaptive speckle filters and structure detection processes which consider a uncorrelated speckle model.

Fig. 2 shows the image filtered by means of the structure retaining Gamma-Gamma MAP filter [1]. This image, where speckle is drastically removed shows an excellent preservation of structural elements. Nevertheless, the anaesthetic "crumpled paper" effect judged undesirable by some users is clearly visible.

Fig. 3 is the filtered image using the textural filter based on the GLCM "mean" feature for $S=(\Delta a,\Delta r)=(+2,-1)$, in order to deal with the correlation introduced by the relationship between resolution cell and pixel size in range and azimuth (c.f. §3). Texture, already preserved by the preceding step in Fig.2, is enhanced in this image Nevertheless, some blurring is introduced near scene structures.

Fig.4 is the filtered image, where scene ACF evaluation is used to estimate the very local estimate of the mean radar reflectivity (c.f. §4). Speckle reduction on homogeneous areas in comparable to that on Fig.2. Structures are also as sharply detected as in Fig.2. But, undesirable effect arising from the structure detection process disappear due to the gradual variation of the radar reflectivity near structures. The resulting effect is visually close to the appearance of optical images.

A simple upgrade of the structure retaining Gamma-Gamma MAP filtered image in Fig.2, using an exponential filter with locally computed decay constants (c.f. §5, case 2) gives a result comparable to Fig.4, probably due to scene correlation properties at the ERS-1 resolution.

7. Conclusion

The introduction of second order statistics of the speckle and the underlying scene into a structure retaining speckle filter for SAR images allows to consider speckle correlation for filtering purpose, and to estimate correctly the very local first order statistics of textured scenes according to the NMNV scene model. Ideally, the estimation of the very local $<R>$ and C_R must be done before the filtering and radiometric restoration process (MAP or MMSE estimate), in order to preserve small scale fluctuations of the reflectivity due to texture.

Since adaptive filters based on scene heterogeneity [6] are able to preserve some textural properties, a textural filter can be applied to a classically filtered image, in order to enhance partially damaged but recoverable textural properties, in the case of coarse textures. This can be performed using either Haralick features of the GLCM, or an exponential filter with appropriate decay constants, applied on a very small window size.

Restoration of radiometric and scene textural properties results in filtered images, visually comparable to optical images, allowing both easier photo-interpretation and better use of textural properties for class discrimination in computer based classifications [17].

Acknowledgement

This research has been conducted at JRC/IRSA-Ispra, within the Agricultural Information System Unit, under a post-doctoral EEC grant.

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Figures :

Figure 1 : 3-looks FDC ERS-1 image of the area of Seville (Spain) acquired on 1st July 1992 (© ESA 1992).

Figure 2 : ERS-1 image filtered using the structure retaining Gamma-Gamma MAP filter [1]. Window size of 9x9 pixels.

Figure 3 : Application of the textural filter based on a GLCM feature ("mean", S=(Δa,Δr)=(+2,-1), window size of 5x5 pixels), to Fig.2.

Figure 4 : Image filtered using the structure retaining Gamma-Gamma MAP filter, where scene ACF evaluation is used to estimate the local mean radar reflectivity.

Figures are to be found in the paperbound issue of the Proceedings of IGARSS'94, and in the scanned text version of the paper, on this disk.